Image Reconstruction Algorithm for Electrical Impedance Tomography Using Group Sparsity

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ABSTRACT

Electrical Impedance Tomography (EIT) is one of electrical tomography modalities for non-intrusive, high-temporal-resolution conductivity imaging. Attributing to its superior characteristics, EIT has found it extensive research and applications in both industrial and biomedical fields. Despite its high temporal resolution, improvement for the relatively low reconstructed image quality in practical situations is intensely desired and has become a research focus for long. In this paper, an image reconstruction algorithm based on group sparsity constraint is introduced. As an extension of standard sparsity concept, the idea of group sparsity has been come up with in recent years, which further takes advantage of the fact that in many cases the non-zero coefficients in the reconstructed signal or image tend to be clustered rather than randomly distributed. In standard sparsity prior, a constraint on non-zeros is applied for the whole target image. While in EIT, conductivity variance usually appears as groups. Therefore, clustered sparsity prior is expected to be more effective to promote image feature than the standard sparsity regularization in EIT imaging. Motivated by this idea, the image reconstruction framework based on group sparsity for EIT is proposed and grouping methods is presented. Numerical analysis is performed on small scale conductivity phantoms to validate the algorithm. Furthermore, static experiments by our developed EIT system is also carried out. Comparison between the proposed algorithm and conventional Landweber method verifies the performance of proposed algorithm.

Keywords Electrical impedance tomography, group sparsity, image reconstruction.

1 INTRODUCTION

Capable of spatial and temporal impedance variance imaging, Electrical Impedance Tomography (EIT) has been extensively studied in biomedical (Holder 2004) and industrial applications (Dickin et al 1996; Sharifi et al 2013) to visualize process parameters related to conductivity variance. Compared with other tomography modalities, e.g., x-ray tomography and optical tomography, the benefit of EIT includes non-intrusive sensing, ultra-high temporal resolution (more than 500 frames per second), free of radiation, and low cost. Beyond that, EIT can be extended for multi-frequency sensing, thus provides extra information in a frequency domain. Since the first initiative of EIT, tremendous progress has been made in forward problem modelling, image reconstruction algorithm development, instrumentation, and application study. However, low spatial resolution still remains a bottleneck of EIT, especially in the scenarios dealing with small scale conductivity variance or demanding high quality images for quantitative evaluation. Although a great number of work to address the bottleneck was reported (Lionheart 2004), few has investigated effective image reconstruction algorithms for small scale conductivity variance estimation.

Targeting at small scale conductivity variance imaging, in this paper we propose an image reconstruction algorithm for EIT based on group sparsity constraint. As an emerging concept in signal and image processing, constraint based on sparsity representation (Candes et al 2007; Mairal et al. 2008) has gained great popularity in facial recognition, medical imaging, analog-to-information conversion, communication, geophysical data analysis, and computational biology, etc. The standard sparsity constraint treats the target image or signal as a whole and attempts to seek an orthogonal basis to decompose the target image or signal. The decomposition coefficients are expected to be sparser than the original one thus better imaging results can be obtained. In the standard method, only sparsity is utilized as prior information. However, as observed, in some practical cases the non-zero coefficients in sparse data set usually tend to be clustered rather than randomly distributed. On the basis, the concept of group sparsity is further investigated by Huang and Zhang (2010). Group sparsity aims at utilizing both sparsity and cluster as prior information rather than only sparsity in conventional methods. In EIT, the small scale conductivity variance usually occurs sparsely and in cluster, yet prior information is not fully utilized in the past work. Motivated by the idea, image reconstruction algorithm based on group sparsity for EIT is proposed and grouping methods is studied. Numerical analysis is performed on several small scale conductivity variance phantoms to evaluate this algorithm. Furthermore, static experiments by using our in-house developed multi-frequency EIT platform are also carried out. Both simulation and experiment results of group sparsity show significant improvement on the spatial resolution of tomographic image compared with those of Landweber iteration (Yang et al. 1999).

2 PRINCIPLE AND METHOD

In EIT, the linearized relationship between conductivity in the sensing domain and boundary voltage on electrodes can be formulated as

$$v = Jx + e \tag{1}$$

where v is boundary voltage data measured on electrodes; J is Jacobian matrix; x is conductivity distribution inside the sensing domain; e is measurement noise. The process of EIT image reconstruction is to determine x on the basis of pre-calculated J and measured v. Conventional Landweber iteration method (Yang et al. 1999) is expressed as

$$x_{k+1} = x_k - \alpha J^{\mathrm{T}}(Jx_k - v) \tag{2}$$

where x_{k+1} and x_{k+1} are estimation of conductivity distribution at step k and step k+1, respectively; α is iteration step factor. In this work, the initial value of x is set as a zero vector. The result of using Landweber iteration is for comparison purpose in this paper.

Given that the image x is divided into m disjoint groups as $\{x_{s_1}, x_{s_2}, \ldots, x_{s_m}\}$ and $\cup_{i=1}^{m} x_{s_i} = x$, the EIT-image-reconstruction problem using group sparsity can be formulated as the following basis pursuit denoise problem

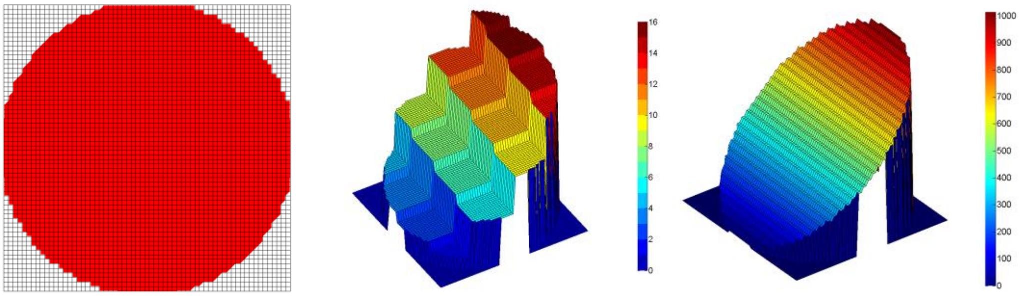
$$\min \sum_{i=1}^{m} \| x_{s_i} \|_2 \quad subject\,to \quad \| v - Jx \|_2^2 \le \tau \tag{3}$$

where τ is a non-negative scalar. If the number of groups m equals to the total pixel number in x, (3) will degrade into the standard sparsity based basis pursuit denoise problem. The problem in (3) is solved by the method proposed by Van Den Berg and Michael (2008).

In this work, a mesh with 64×64 pixels (the setup will result in 3228 pixels in the sensing region) are used to solve (3), as illustrated in Fig. 1(a). The mesh is then equally partitioned in horizontal and vertical directions to form clustered pixel groups, e.g., a 4×4 grouping cluster shown in Fig. 1(b). A group index starts from 1 and successively increases to 16. Each group is illustrated in a different colour based on the index value. In this work, a 32×32 grouping method is adopted as illustrated in Fig. 1(c). Therefore, there will be 2×2 individual pixels in each group (except for the groups near the circular edge) and there are 1024 groups in total. The group index m then ranges from 1 to 1024.

3 RESULTS AND DISCUSSION

Simulation study of several small scale conductivity variance phantoms was performed to analytically evaluate the proposed image reconstruction algorithm. Additionally, a series of static experiments were carried out as well for practical performance assessment.

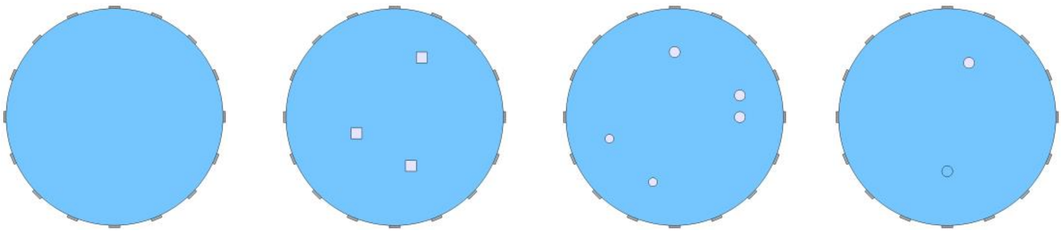


(a) (b) (c)

Figure 1. Mesh and grouping method: (a) mesh; (b) 4×4 grouping cluster; (c) 32*32 grouping cluster.

3.1 Simulation Results

Fig. 2 illustrates three test phantoms with small scale conductivity variance used in the simulation study. A 16-electrode EIT sensor as shown in Fig. 2(a) is modelled. Adjacent sensing strategy is applied and as a result 104 independent measurements can be obtained for one frame image reconstruction. In all phantoms, saline with conductivity of 0.05 S/m is set as background substance. For phantoms depicted in Fig. 2(b) and Fig. 2(c), conductivity abnormity is set as 0.0001 S/m. While in Fig. 2(d), the abnormity near the top has the conductivity of 0.0001 S/m, and the one near the bottom has the conductivity value of 0.5 S/m.



(a) (b) (c) (d)

Figure 2. Conductivity phantoms used in simulation: (a) sensor model; (b) phantom 1; (c) phantom 2; (d) phantom 3.

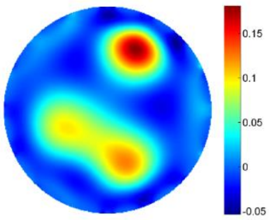
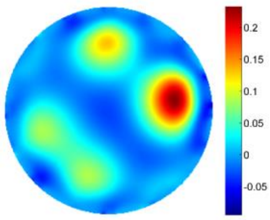
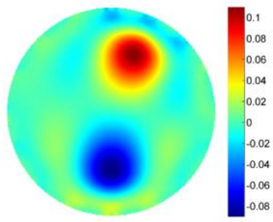
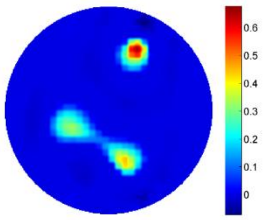
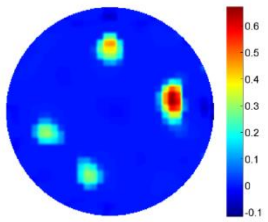
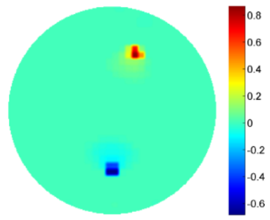
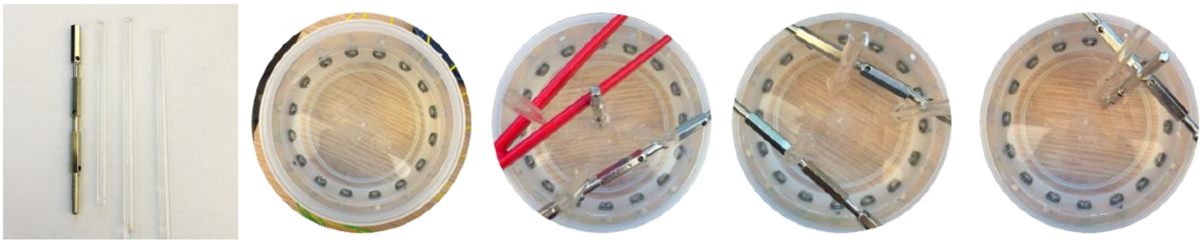
Algorithm	Phantom 1	Phantom 2	Phantom 3
Landweber ($\boldsymbol{n}$=200, $\boldsymbol{\alpha}$ =5)			
Group sparsity ($\boldsymbol{n}$=200)			

Figure 3. Image reconstruction results using Landweber and group sparsity based on simulation data.

Image reconstruction results using the proposed algorithm and Landweber iteration are shown in Fig. 3. For all test phantoms, iteration step factor α is set to 5 and iteration number is fixed at 200 in Landweber iteration. In group sparsity based algorithm, the iteration number is fixed at 200 for all phantoms as well. Accurate estimation of conductivity abnormity with small dimensions has become a challenge for long. With regard to the given phantoms, it is shown that the conventional algorithm, Landweber iteration, is limited to only roughly demonstrate the position and amplitude of small conductivity abnormity. Whilst the image is seriously blurred and plenty of artefact exists. Such results can only be used for qualitative analysis attributing to low image quality and inaccurate information. By introducing group sparsity, the results shown in Fig. 3 indicate significant improvement in aspects of reduced artefact, accurate position, and clear boundary. The simulation validates the feasibility of applying proposed algorithm in small scale conductivity variance imaging, which extensively exists in practical situation.

3.2 Experiment Results

The performance of proposed algorithm is assessed by a series of static experiments. Fig. 4 illustrates the target test objects, the EIT sensor and three test phantoms used in experiments. The glass tubes having a diameter of 6 mm serve as non-conductive objects. The hexahedron metallic pillar with a diameter of 6 mm serves as conductive objects. A 16-electrode EIT sensor depicted in Fig. 4(b) has a diameter of 95 mm. Hence, the diameter ratio of an individual object with respect to the sensor is approximately 6.3%. Tap water with the conductivity of 0.0241 S/m is used as background substance. Adjacent sensing strategy is applied. The measurements are taken by an in-house designed multi-frequency EIT system. In all tests, current excitation frequency is fixed at 20 kHz, and current amplitude is fixed at 3.7 mA peak to peak.



(a) (b) (c) (d) (e)

Figure 4. Experiment phantoms: (a) target objects; (b) sensor; (c) phantom 1; (d) phantom 2; (e) phantom 3.

Fig. 5 shows the image reconstruction results of the test phantoms by Landweber iteration and proposed group sparsity based algorithm. The same algorithm parameters are adopted in experiments as in simulation. From the experiment results, consistent conclusion can be drawn with the simulation results. Compared with the blurred, artefact-contaminated images by using Landweber iteration, the proposed method generates high quality images for all the test phantoms with clear boundary, accurate location and less artefact. The experiment results further verify the practical performance of proposed method with improved spatial resolution.

4 CONCLUSION

In this paper, we propose an image reconstruction algorithm for electrical impedance tomography based on group sparsity constraint. The aim is to improve spatial resolution for applications with small scale conductivity variance, which commonly appears in practical situation but has been a challenging problem for long. A preliminary grouping method is proposed and basis pursuit denoise method is applied to solve the optimization problem. The developed method is evaluated by phantoms and experiments composed of multiple objects with object-sensor diameter ratio of 6.3%. Both simulation and experiments results indicate that the proposed method is able to significantly improve the spatial resolution for small scale conductivity variance compared with conventional Landweber iteration method. Future work will further investigate adaptive and dynamic grouping methods to maximize the sparsity of the target image.

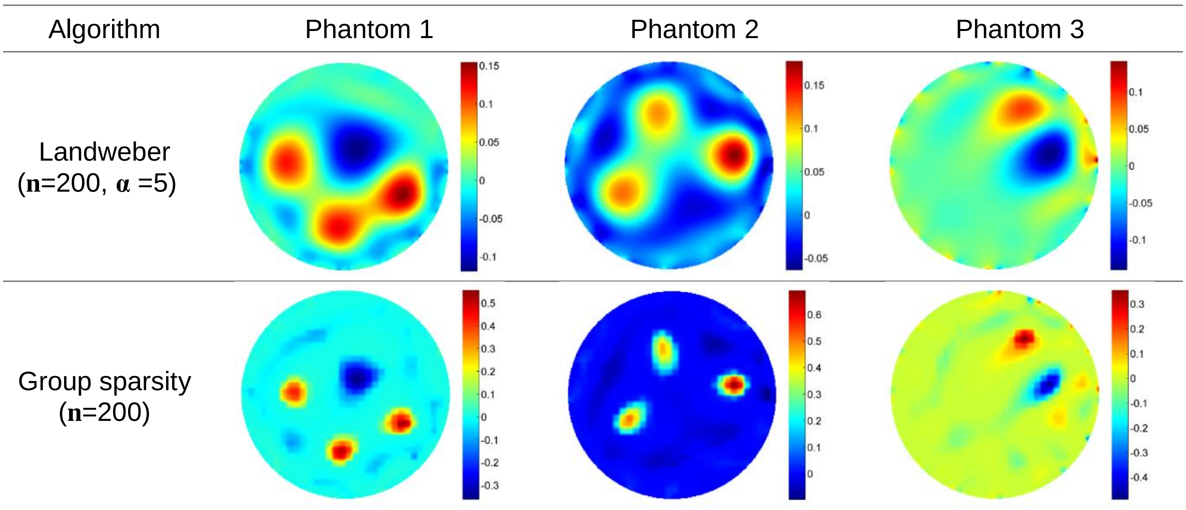


Figure 5. Image reconstruction results using Landweber and group sparsity based on experimental data.

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